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# Real Time wave forecasting using artificial neural network with varying input parameter

J. Vimala[1], G. Latha[2] & R. Venkatesan[2]

[1]Sathyabama University, Chennai-600 119, India.
[2]National Institute of Ocean Technology Chennai-600 100, India.
[E-mail: vimalanerur@yahoo.co.in]

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Prediction of significant wave heights (Hs) is of immense importance in ocean and coastal engineering applications. The aim of this study is to predict significant wave height values at buoy locations with the lead time of 3,6,12 and 24 hours using past observations of wind and wave parameters applying Artificial Neural Network. Although there exists a number of wave height estimation models, they do not consider all causative factors without any approximation and consequently their results are more or less a general approximation of the overall dynamic behaviour. Since soft computing techniques are totally data driven, based on the duration of the data availability they can be used for prediction. In the National data buoy program of National institute of Ocean Technology, not all the buoys have wind sensors and wave sensors and so it is attempted to apply neural network algorithms for prediction of wave heights using wind speed only as the input and then using only wave height as the input. The measurement made by the data buoy at DS3 location in Bay of Bengal (12$^{o}$11'21"N and 90$^{o}$43'33"E) are considered, for the period 2003 - 2004. Out of this, the data of period Jan 2003-Dec 2003 was used for training and the data for the period July 2004- Nov 2004 is used for testing. Real time wave forecasting for 3,6,12 and 24 hours were carried out for a month at the location chosen and the results show that the ANN technique proves encouraging for wave forecasting. Performance of ANN for varying inputs have been analysed and the results are discussed.

**[Keywords:** ANN, Wave Forecasting, Correlation coefficient, Neural network, Computational elements]

## Introduction

The time series of significant wave heights is essentially random in nature. In order to analyze random data a new approach called soft computing is gaining popularity since last decade. Soft computing essentially utilizes the tolerance of the real world to uncertainties, imprecision, inaccuracies and partial truth associated with the input information in order to come up with robust solutions. Idea before soft computing is human mind. An understanding of the cognition process of human brain is imitated in a soft approach like ANN. ANN's have been successfully applied to make hydrological predictions in last fifteen years while their use in oceanic predictions has started in the last decade only. There is a scope to exploit full potential of ANN's in wave analysis and forecasting. This paper presents the wave forecasting using the wave and wind data measurements at DS3 locations with long period record and through application of artificial neural network. Data sets have been trained, tested and used for forecasting upto 24 hours. This model uses wave and wind as the input and through application of neural network technique wave parameters have been simulated and the results are very good. This paper attempts to do this by employing the technique of neural networks. The connection between the artificial and the real thing is also investigated and explained. In this study, neural network strategies are employed to forecast significant wave heights for 3, 6, 12, & 24 hours in advance.

## Materials and Methods

The neural networks used in this study are of common feed forward type exemplified in Fig. 1. It has an input layer, two hidden layers and an output layer. Each layer consists of computational elements or neurons where the basic action is to combine the weighted input from the preceding layer neurons (also called nodes), add a bias term, transform the summation through a transfer function and pass on the results to the neurons of the subsequent layer.

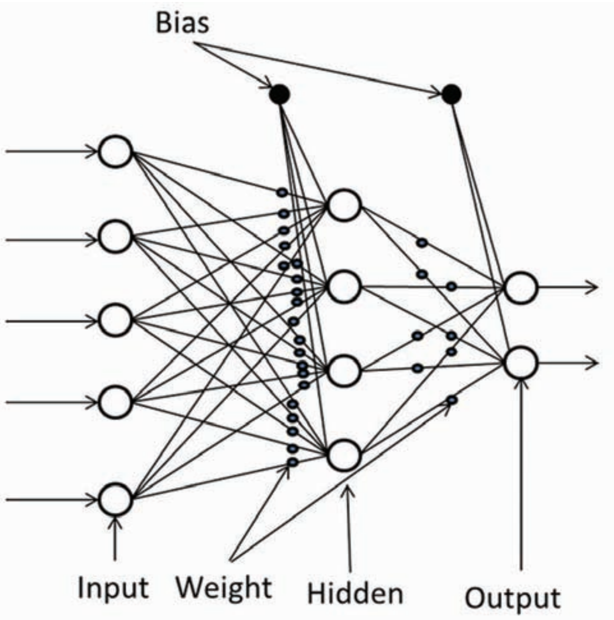


Fig. 1–Feed Forward Neural Network

Processed output from neurons belonging to the output layer represents the outcome from the network. Further details of networks can be seen in textbooks such as Kosko (1992) and Wu (1994) and Wassermann (1998). A review of NN applications in ocean engineering can be seen in Jain and Deo (2006).

**Working of a neural network**

A neural network basically consists of three sets of units namely input units, hidden units and output units. Theoretically each layer may contain any number of elements. Systems can have more than three layers in which case the number of hidden layer would be more than one.

A typical neural network represents interconnection of computational elements called neurons or nodes, each of which basically carries out the task of combining the input, determining its strength by comparing the combination with a bias (or alternatively passing it through a non-linear transfer function) and firing out the result in proportion to such a strength.

Mathematically,

$$y = f\left[\sum(x_1 w_1 + x_2 w_2 + ...) + \theta\right]$$

y=output of the neuron; x1, x2, x3,...= input values; w1, w2, w3,...= connection weights that determine the strengths of the connection; θ = bias value, which increases the net input to the activation function, and, thus, accelerates the error convergence; and f = transfer, activation or squashing function, which controls the output of a neuron or squashes it to a nite range like (0,1) or (-11). A majority of the networks use the sigmoid function given by,

$$f[\bullet] = \frac{1}{1+e^{-[\bullet]}}$$

Other forms, like purelin function given by,

$$f[\bullet]=[\bullet].$$

**Site description and data collection**

Several deep-sea and shallow water moored buoys have been functional in the north Indian Ocean since 1997 under the National Data Buoy Program (NDBP), National Institute of Ocean Technology (NIOT). In the present study, we have used wave and wind data measured by the deep-sea buoys operating in the Bay of Bengal at 12º11'20"N /90º43'30"E. Wind reported wind magnitudes are averages of 600 samples (measurements acquired over 10 minutes with sampling speed of 1 sample/second). Sensor used in the sensor was installed at ~3m above sea surface. The measurement of signicant wave height is an inertial altitude heading reference system with dynamic linear motion measurement capability. Its accuracy is ±20 cm and resolution 1 cm.

| | |
|---|---|
| Latitude (deg N) | :$12^{O}$ 11' 20"N |
| Longitude (deg E) | :$90^{O}$ 43' 30"E |
| Depth | :3100 meters |

Data used were significant wave heights, wind speed, wave period for the time period 2003-2004. Out of this, the data of period Jan 2003-Dec 2003 was used for training and the data for the period July 2004- Nov 2004 is used for testing (Table 1).

Once the required data was collected, the development of the model was done using artificial neural networks. MATLAB was used for implementing ANN. In all the cases, TRAINLM was the adopted network training function. TRAINLM is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. All input and output values were normalized within the range of -1 to 1. All weights and bias values were initialized to a value of 1. The transfer function used was logarithmic sigmoid, uniformly for first hidden and output nodes and purelin transfer function used for second hidden and output nodes. Other details of the network architecture

Table 1–Number of data used

| Data Set | No. of Data used |
|---|---|
| Training set | 2920 |
| Testing set | 1150 |

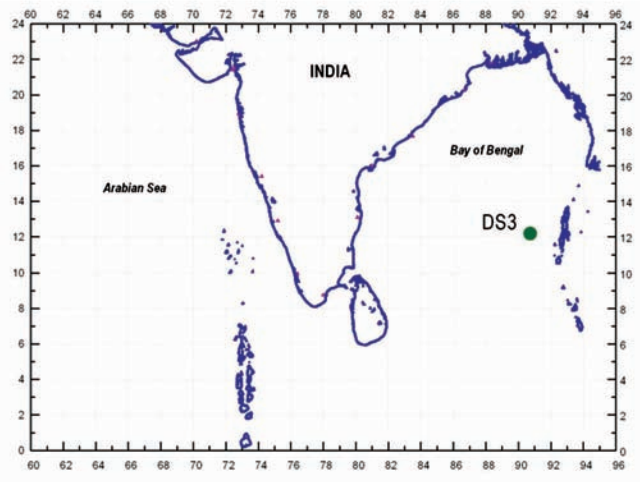


Fig. 2–Buoy Location

chosen for each of the location are given under results section. The developed model was verified in each case and the details are given in results section.

**Result and Discussion**

The closeness of the predictions with the actual observations was judged qualitatively from time series comparison plots and quantitatively by evaluating three error measures, namely, the correlation coefficient, R, the mean square error MSE and the absolute mean error, MAE.

The verification statistics show that values of Hs are simulated well when short predication intervals of three and six hours are concerned.

Time series plot between the Forecasted Wave height and observed significant wave height is given below:

*Wave data input To Wave Forecasting*

This model uses the wave as the input and using Artificial Neural Network is carried out on wave forecasting. Fig. 3 shows the time series plot of Predicted vs. Observed significant wave height. The correlation coefficient (CC) as well as MSE and MAE continue to deteriorate, indicating again increasing complexity in the input-output structure.

Time series of the forecasted three hourly Hs with the measured three hourly Hs show that the forecasted waves are closely matching with the

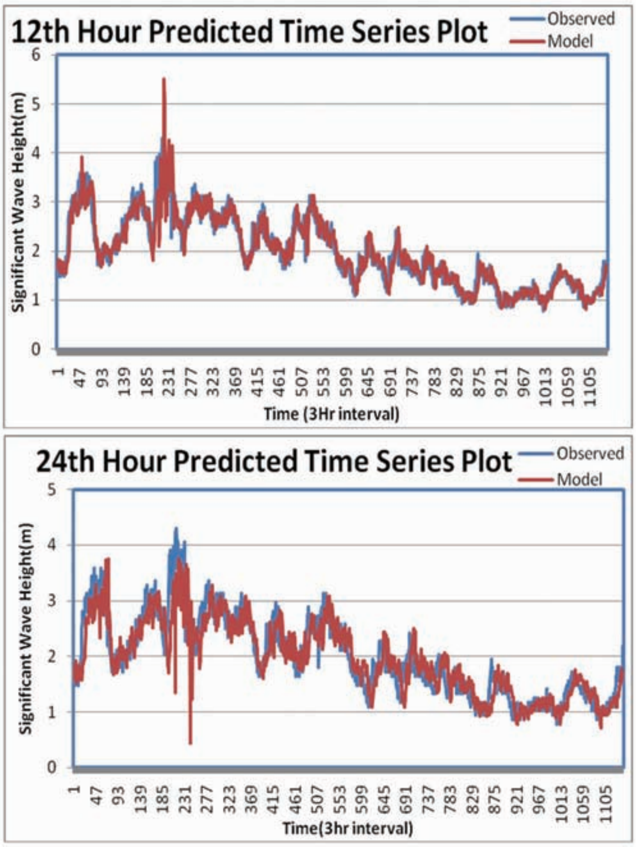


Fig. 3–Time series plot between Observed value and Model Output

measured values. Three hourly waves forecasting by memorization network has estimated the CC of 0.98 (Fig. 3). Six hourly averaged significant wave height is forecasted and CC is 0.97. Twelve hourly wave forecasting data yields CC of 0.95. In this also the up and down of wave profile is picked up by the forecast profile. The day forecasting Hs yields the correlation coefficient value of 0.92.

*Wind data input To Wave Forecasting*

The work carried out on wave forecasting uses wind as the input and through application of neural network technique wave parameters have been simulated and the results are very good. The data sets have been trained, tested and used for forecasting upto 24 hours. Coefficient of correlation are higher than or equal to 0.924 showing that the model performs very well for these forecasts whereas for 24 hour prediction the correlation coefficient is 0.899 which is reasonable. Fig. 4 shows, the time series plot between the Forecasted Wave height and observed significant wave height.

The Fig.5 shows correlation coefficient of both wave and wind data input. Wave data input performs much better when compared to wind data input. Comparisons between the network outcome and the target one have been done using both qualitative as well as quantitative measures. Qualitative assessment is made with the help of scatter diagrams or time history plots, where deviation from the ideal fit line across the entire range of predictions is immediately seen (Figs. 3 and 4). A variety of error measures serve the quantitative requirement and they include, among others, the correlation coefficient (CC), mean square error (MSE), mean absolute error (MAE) Table 2.

The correlation coefficient, used normally measures the degree of linear association between the target and the realized outcome and gets heavily affected by the extreme values. Mean square error, MSE, is specially suited to the iterative algorithms and is a better measure of high values; however for assessing the fit at moderate values within the range of the given output the mean square relative error is suitable. Measures involving error square terms are sensitive to extreme values.

*Real Time Implementation*

Model has been applied for real time forecasting at the DS3 location for a period of one month (May 2007) and results of simulations obtained using the networks architecture. For real time models the data sets were prepared on an three hourly basis so that wave height forecasts for next 24 hours may be available from any time. Models were run continuously from 1 May 2007, using the previous day of wave height measurements. Once trained, the ANN models required less than 1 second to provide a forecast.

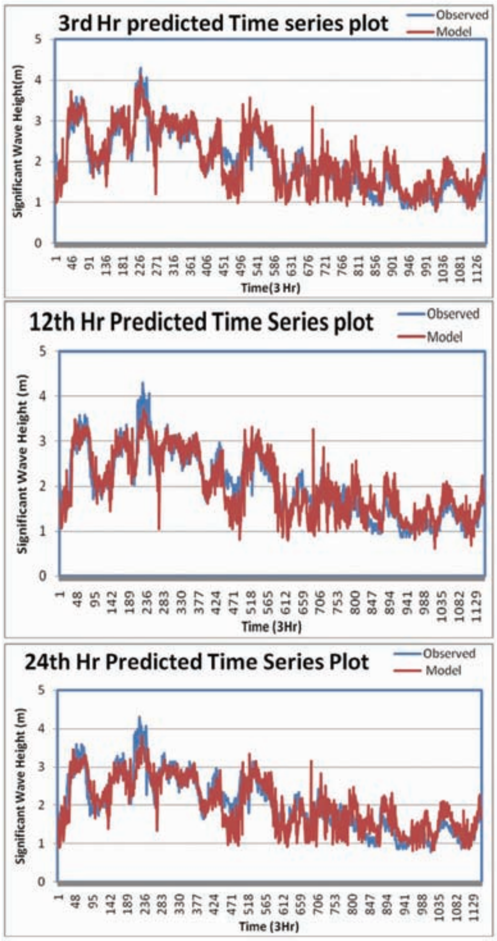


Fig. 4–Time series plot between Observed value and Model Output (wind input)

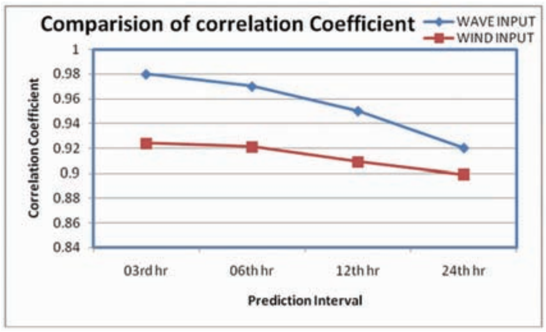


Fig. 5–Correlation Coefficient plot

Table 2–Verification statistics of Hs simulations with different lead times

| Buoy ID | Statistics | 03$^{rd}$ hr | 06$^{th}$ hr | 12$^{th}$ hr | 24$^{th}$ hr |
|---|---|---|---|---|---|
| Wave Input | Correlation Coefficient | 0.98 | 0.97 | 0.95 | 0.92 |
| | MSE | 0.038 | 0.043 | 0.065 | 0.115 |
| | MAE | 0.119 | 0.138 | 0.176 | 0.233 |
| Wind Input | Correlation Coefficient | 0.924 | 0.921 | 0.909 | 0.899 |
| | MSE | 0.038 | 0.043 | 0.065 | 0.115 |
| | MAE | 0.476 | 0.476 | 0.479 | 0.494 |

Fig. 6, the significant wave heights estimated from observations and simulated with different lead times are displayed.

The verification statistics show that values of Hs are simulated well when short predication intervals of three and six hours are concerned (Table 3). Coefficient of correlation are higher than or equal to 0.97 showing that the model performs very well for these forecasts whereas for 24 hour prediction the correlation coefficient is 0.87 which is reasonable.

Table 3–Error statistics for observations

| Buoy | Forecast interval'Hrs' | Correlation coefficient'CC' |
|---|---|---|
| DS3 | 3 | 0.97 |
| | 6 | 0.95 |
| | 12 | 0.93 |
| | 24 | 0.88 |

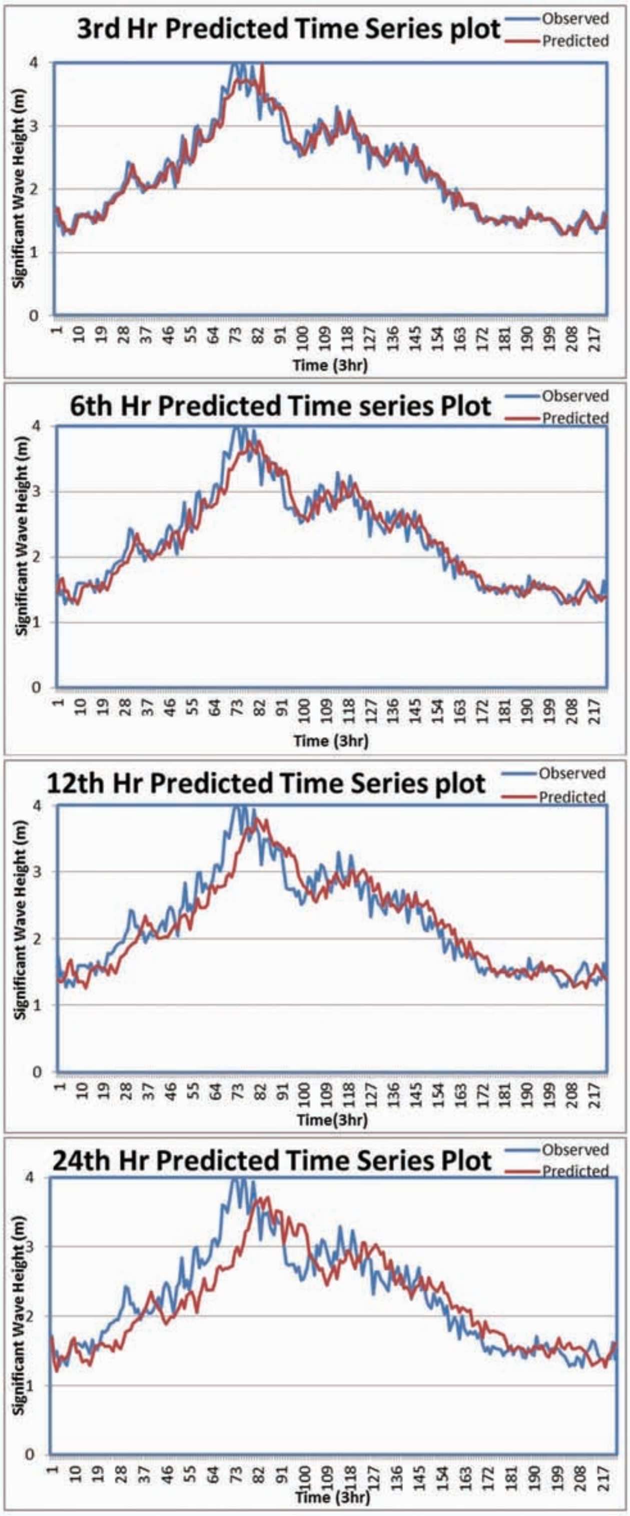


Fig. 6–Time series plot between observed value and model output (Real time)

## Conclusion

Artificial neural networks were used to predict significant wave heights with leading times of 3,6,12, and 24 hours. Simulations were compared to time series of these wave parameters estimated at the buoy location Off Chennai (DS3). Results show different levels of performance of each of the neural networks in terms of the root mean square error and correlation coefficient. The behaviour changed according to the parameter being predicted and the period of forecasting. The nets simulating integral wave parameter and short lead times (three and six hours) performed generally better than the ones developed for longer time periods. Correlation coefficient between Hs from the wave data input and wind data input was significantly high, ranging from 0.899 to 0.98; the highest correlation is in the 3$^{rd}$ hour. This comparison for periods of 2003-2004 proved that the wave data input is suitable to forecast wave heights in the Bay of Bengal using ANN. As the prediction interval increases, correlation coefficient decreases whereas MSE and MAE increase.

Also since the results are encouraging it is planned to use the technique for different buoy sites in Arabian Sea and Bay of Bengal so that wave forecasting in real time could be used and applied for operational purposes.

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